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Expectation Formation and the Financial Ratio Adjustment Processes

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ABSTRACT

This paper analyzes the adjustment processes of financial ratios in the presence of costly adjustment and information uncertainty. The paper proposes a generalized partial adjustment-adaptive expectations model to characterize the dynamic financial ratio adjustment processes. The proposed model incorporates the manager's assessment of the persistency of changes in industry averages into the process of financial ratio adjustment. It is found that Lev's [1969] partial adjustment model is a special case of the proposed generalized model. The Gauss-Newton nonlinear regression method is used to estimate the structural parameters of the generalized model. Results show that managers do not always adjust their desired target ratios instantaneously when industry averages are variable. Results also show that there are differences in the patterns of ratio adjustment for firms in different industries and with different sizes. Empirical results show that the generalized model better explains firms' financial ratio adjustment process.

Expectation Formation and the Financial Ratio Adjustment Processes

In traditional accounting and finance analysis, firm's financial ratios are often related to some predetermined targets which are usually based on industry norms. Empirical evidence (see Lev [1969] and Frecka and Lee [1983]) has generally indicated that firms do adjust their financial ratios to industry norms. The causes of this dynamic adjustment have usually been attributed to either active attempts by management or passive industry-wide effects operating on the firm.

Although there is some evidence on the periodical adjustment of key financial ratios, so far there has been lack of a consensus on the pattern of the underlying adjustment process. Lev [1969] employs a partial adjustment model to characterize the dynamic financial ratio adjustment process while Frecka and Lee [1983] assume a generalized functional form that includes linear and log-linear adjustment processes as the special cases. In both studies, the desired target ratios are assumed to be the past or current industry averages.

The determination of the correct target ratios is important for the analysis of financial ratio adjustment. Studies (see Waud [1966], Doran and Griffith [1978]) have shown that the way managers forecast their desired targets can actually affect the pattern of ratio adjustment process. Recently, Moses [1987] also indicates that the relative magnitude of the expected and unexpected earnings components can affect the manager's choices of accounting procedures and ultimately affect the financial ratios and other accounting information reported. Lev has recognized that potential problems may arise from using a past or current industry average as the firm's target ratio to examine the ratio adjustment process when the true desired target is not observed. However, no specific remedy was proposed for coping with these problems because of the difficulty involved in separating the transitory component from the permanent component of the changes in the industry averages.

The purpose of this paper is to extend Lev's partial adjustment model for ratio adjustment to consider explicitly the formation of desired targets. The paper suggests that the specific pattern of ratio adjustment depends upon the managers' assessment of the current industry conditions. Managers follow an adaptive process to revise their target ratios by responding only to the permanent changes in the industry averages. Along this line, the paper develops a measure of the desired target ratio in accordance with the theory of expectation formation. The ratio adjustment process is then reexamined based on the proposed framework.

The main objectives of developing and testing accounting theory are to explain and predict accounting practice. This paper has partially accomplished these objectives in the area of financial ratio analysis by contributing to our understanding on the pattern of financial ratio adjustments. First, the generalized ratio adjustment model proposed in this paper is capable of explaining a commonly observed practice of adjusting the firm's financial ratios to some targets. As will be shown, the empirical results provided in this paper indicate that the generalized ratio model better explains the dynamic adjustment pattern of financial ratio than the simple partial adjustment model. Financial ratios have been used extensively for bankruptcy prediction (Altman [1968]), credit rating (Pinches and Mingo [1973]), security analysis (Reilly [1987]) and audit evaluation (Altman and McGough [1974]). An important issue of using financial ratios for these purposes is how financial ratios change over time. For instance, bonds usually default after firms' financial conditions have deteriorated and bond issues have been downgraded. Understanding more about the adjustment of ratios for a firm or a group of firms will improve the prediction of bond defaults before they really occur. Doubtlessly, to use financial ratios effectively requires a thorough understanding of their adjustment processes.

Second, the proposed generalized ratio adjustment model has a higher predictive power. Results of this study show that the prediction errors generated by the model are reasonably small. The better forecasting performance implies that the model is a more suitable framework for the prediction of future ratio behavior. The usefulness of a model will be very limited if it has very low predictive ability. The greater predictive power of the generalized ratio model is achieved by explicitly incorporating the process of the formation of expectations concerning future target ratios.

As with many other positive accounting theories, the generalized ratio adjustment model offers potentially important implications for accounting practice. A model with reasonable explanatory and predictive ability should provide relevant information for decision making. Knowing the ratio adjustment process and the formation of desired targets, the managers can choose an available technique or combination of techniques to change the financial ratios in the desired direction. Managers may use appropriate accounting rules to affect financial ratios. For instance, the inventory valuation methods can be used to affect the current ratio. Also, accounting rules can be used to smooth reported income. When the growth of income is above the target, accounting measurement rules (e.g., accounting changes related to accruals or discretionary expenses) which decrease it can be used by the managers. Managers can also include the target ratios in their budgets and control business operations to change the financial ratios toward the budgeted ones. An example is to change the terms of credit sales to achieve a desired target. As pointed out by Lev, the financial ratios can be even changed passively by allowing industry-wide effects to operate on the firms. Although this paper does not intend to investigate these complex techniques, the analyses herein should provide assistance in selecting potentially useful techniques for ratio adjustments.

The remainder of this paper is divided into four sections. Section 1 discusses the importance of considering the expectation formation in analyzing the financial ratio adjustment. A cohesive model consistent with the partial adjustment and adaptive expectations processes is formulated. Section 2 describes the estimation methodology and the data used. Section 3 reports key empirical results. Section 4 concludes the paper.

1. A Generalized Financial Ratio Adjustment Model

The partial adjustment model employed by Lev [1969] can be expressed as

$$y_t - y_{t-1} = \lambda(y_t^* - y_{t-1}), \quad 0 < \lambda \leq 1 \tag{1}$$

where

y_t = a firm's financial ratio in period t

y_{t-1} = a firm's financial ratio in period t-1

y_t^* = the target level of a particular ratio

λ = the speed of adjustment coefficient

Equation (1) states that the current level of financial ratio, y_t, will move only partially from the previous position, y_{t-1}, to the target level, y_t^*. The amount of adjustment between time t and t-1 is equal to $\lambda(y_t^* - y_{t-1})$, where the fraction λ measures the speed of adjustment.[1] The size of λ reflects the limitations to adjustment caused by technological and institutional constraints.

Lev set

$$y_t^* = x_k, \; k = t \text{ or } t-1 \tag{2}$$

where x_k is the industry average of a particular financial ratio at time t or t-1.[2] Lev has found that the empirical results in terms of R^2 and the t-statistics for λ were better when x_t was directly used as the target level. Clearly, the magnitude of adjustment depends on both λ and y_t^*. As indicated by Lev, a major question facing the firm is the interpretation of any recent change in the industry mean. A change in industry mean can either be a permanent change or just a transitory fluctuation. The firm's financial ratio adjustment would depend on the manager's assessment on the persistency of the current change in industry mean. If the change is largely transitory, which often happens when the industry mean is highly variable, then the adjustment is expected to be relatively small. Conversely, if the change in the industry mean is permanent, the adjustment would be relatively large.

A possible way to incorporate the expected persistency of the change in industry average into the ratio adjustment model is to specify formally a process for the formation of expectations. The specific process of expectation formation considered here is adaptive expectations. More specifically, let

$$y_t^* - y_{t-1}^* = \delta(x_t - y_{t-1}^*) \tag{3}$$

or, equivalently,

$$y_t^* = \delta x_t + (1-\delta)y_{t-1}^* \tag{4}$$

where δ, the coefficient of expectations, is the proportion of the current change in industry average taken to be permanent rather than transitory (see Waud [1966]).[3] The target level is updated each period by a fraction of the discrepancy between the current level of industry average and the previous target level.

The adjustment process of the target ratio expectations specified in equation (4) implicitly assumes that corporate managers revise their expectations gradually. The magnitude of revision depends on the size of δ. The coefficient of expectations δ is the proportion of the expectational error taken to be permanent rather than transitory. High value of δ implies substantial adjustment in expectations and low value of δ implies slowly changing expectations. When δ is equal to zero, the expected target ratio is characterized by a process with a constant expectation. When δ is equal to one, the expected target ratio is adjusted instantaneously to the current level of industry mean. Intermediate δ values imply the dependence of expected target ratio on the current industry mean.

Recursively substituting the values of y^*_{t-1}, y^*_{t-2}, ... and y^*_{t-s} into the right-hand side of equation (4) gives:

$$y^*_t = \delta[x_t+(1-\delta)x_{t-1}+(1-\delta)^2x_{t-2}+\ldots+(1-\delta)^sx_{t-s}] = \delta x_t+(1-\delta)y^*_{t-1} \quad (5)$$

Thus, the adaptive expectation model implies that the expected target ratio for any given year is an exponentially weighted moving average (EWMA) of past observed industry averages. According to the adaptive model, recent values of industrial averages are weighted more heavily in the moving average. This hypothesis for expectation formation process would seem to be more reasonable than Lev's naive specification (using just the industry average lagged by one period) or any simple moving average of past industry averages, since a rational forecaster will probably place a heavier weight on the most recent information.

Equation (4) can be written as

$$(1 - \phi L)\, y_t^* = \delta x_t \tag{4a}$$

where $\phi = 1 - \delta$ and L is the lag operator. The target ratio forecast follows an AR(1) process if x_t is a white noise. In general, the time series process of the target ratio forecast depends on the process of current industry average. For instance, if x_t follows a moving average process of order q, y_t^* will follow an ARMA (1,q) process. Muth [1960] has shown that this forecast (for the unobserved target ratio) is the best linear forecast (in terms of the sum of squared error minimization) when x_t follows an MA(∞) process

$$x_t = e_t + \theta \sum_{i=1}^{\infty} e_{t-i}, \tag{4b}$$

where e_t are random shocks independently distributed with mean zero and variance σ^2.

The adaptive model has been used extensively in the accounting and economic literature to describe the formation of expectations concerning future behavior of financial and economic variables. The hypothesis of adaptive expectations has considerable empirical support. Brown and Rozeff [1979], and Givoly [1985] have found that adaptive model describes adequately the process of the formation of earning forecasts. Turnovsky [1970], and Figlewski and Wachtel [1981] have found that inflation expectations are formed in an adaptive way. Pettit [1972] has indicated that a change in dividend policy is a result of a change in the expectations of long run expected income rather than a temporary change in current income. Lee, Wu and Djarraya [1987] provide evidence that dividend forecasts follow an adaptive process. Ball and Watts [1972] have found that the adaptive expectation model of (4) best fits the time series process of sales. In addition, they found that the δ value of the time series deflated net income is less than one. Thus, the specification of changes in the expectations in equation (4) seems consistent with practical decision-making processes. Managers maintaining stable financial policy tend to ignore transient fluctuations and adjust their forecasts adaptively. Equation (4) permits estimation of δ from actual time series data. The estimated δ value will reflect management's assessment of the persistency of current industrial ratio changes.

Substituting (5) into equation (1) yields:

$$y_t = \lambda\delta[x_t+(1-\delta)x_{t-1}+(1-\delta)^2x_{t-2}+\dots+(1-\delta)^s x_{t-s}] + (1-\lambda)y_{t-1} \quad (6)$$

Using Koyck transformation, equation (6) can be simplified as

$$y_t - y_{t-1} = \lambda\delta x_t + (1-\lambda-\delta)y_{t-1} - (1-\delta)(1-\lambda)y_{t-2} \quad (7)$$

Equation (7) characterizes the adjustment process of financial ratios in terms of the partial adjustment due to technological and institutional constraints and the adaptive expectations due to uncertainty and discounting of current information. If the coefficient of expectation, δ, is equal to unity, then equation (7) reduces to

$$y_t - y_{t-1} = \lambda(x_t-y_{t-1}) \quad (1')$$

Equation (1') is one version of Lev's partial ratio adjustment model. Thus, when the change in the industry mean is considered as permanent, the firm's revision of financial ratios will follow a simple partial adjustment process.[4] Hence, equation (7) represents a generalized case of Lev's model.

Note that the specification of y_t^* in equation (4) is somewhat different from that of Lev [1969]. Lev proposed two main alternatives for the target ratio, as indicated in equation (2). Lev also suggested that a fixed deviation from the industry average can be allowed. That is, $y_t^* = bx_{t-1}$ where b is a constant to measure the discrepancy. In contrast, equation (4) specifies y_t^* as the weighted average of the current and past industry averages where the weights are to be estimated from the actual data. The specification in equation (4) in some sense is more general and less arbitrary.

An estimate model can then be formulated based on equation (7) as:

$$y_t = a_0 + a_1 x_t + a_2 y_{t-1} + a_3 y_{t-2} + u_t \tag{8}$$

where

$$a_1 = \lambda\delta$$

$$a_2 = 2 - \lambda - \delta$$

$$a_3 = -(1-\lambda)(1-\delta)$$

and a_0 is the intercept term; u_t is the disturbance term. The disturbance term u_t may be serially correlated. Moreover, the regression model is nonlinear in the parameters. To obtain consistent and efficient estimates of the structure parameters δ and λ, a nonlinear regression method will be employed while taking into consideration the behavior of the disturbance term.

2. Estimation Procedure and Data

The Gauss-Newton nonlinear least squares regression method is used to estimate the structural parameters of equation (8).[5] However, the Gauss-

Newton procedure converges very slowly for some firms in the sample. In slow converging cases, the Marquardt procedure is often proven to be a useful alternative method for obtaining convergence. As indicated in Draper and Smith [1966, p.272], Marquardt's method combines the basic features of both the steepest descent and Gauss-Newton methods.

Marquardt's procedure starts out exactly the same way as does the Gauss-Newton method. The major difference between these two methods is that Marquardt's procedure includes a correction factor, α, before estimating the parameters of the equation. This correction factor is set to zero for the first iteration and remains zero for all subsequent iterations as long as the sum of squared residual errors is reduced.[6] Therefore, when α is equal to zero, the Marquardt method is identical to the Gauss-Newton method. Nevertheless, if at some iteration i, the sum of squared residual errors is increased, the value of α will be corrected repeatedly until the sum of squared errors is reduced. This method does not slow down as it approaches the solution and in some cases it converges more quickly than the Gauss-Newton method. Therefore, Marquardt's method was used when Gauss-Newton's method can not converge quickly. Both Marquardt and Gauss-Newton subroutines are available in the SAS Libraries.

As with any nonlinear regression method, the selection of appropriate initial parameter values is important. The initial estimates of the parameters were obtained from the maximum likelihood procedure proposed by Zellner and Geisel [1970]. Details of this procedure are available from the authors.

The disturbance term u_t may be serially correlated, or uncorrelated. Both cases for u_t (with and without serial correlation) are considered in estimating the regression coefficients.

Data were obtained from Standard and Poor's Compustat tape for the period 1966-85. The Compustat's four-digit industrial classification is used as the basis for classifying industry groups. The sample contains the data for the firms with no missing financial data for the entire 20 years. Also, a restriction is imposed that at least 10 firms are contained in each industry. This results in 112 firms in eight four-digit industries.

Similar to Lev [1969], the following six ratios were chosen to represent the popular categories of ratios:

Category	Ratio Chosen
Short-term liquidity	1. Quick ratio
	2. Current ratio
Long-term solvency	3. Equity to total debt ratio
Short-term capital turnover	4. Sales to inventory ratio
Long-term capital turnover	5. Sales to total assets ratio
Return on investment	6. Net operating income to total assets ratio

As a proxy for the target ratio, industry averages are computed using the arithmetic means of each industry group. The selection of the same financial ratios as in Lev's study provides a mean for comparison and for examining the effect of expectation formation process on the financial ratio adjustment.

3. Empirical Results

Estimating Regression Parameters

Equation (8) was first estimated by the ordinary least squares regression (OLS) before turning to the more complicated nonlinear regression. The purpose of this exercise is to detect whether there is an indication of expectation adjustment lag. If the coefficients of y_{t-2} are significant, it will imply that expectation is not adjusted instantaneously (δ is not equal to one) and equation (8) is an appropriate model for characterizing ratio adjustment. The estimation of the structural parameters λ and δ by the nonlinear regression is then warranted.

Table 1 summarizes the cross-sectional distribution of the estimates of ordinary least squares regressions. The mean, standard deviation and 9 fractiles are reported for each estimate. As shown in the table, the industrial average x_t is the most important variable in explaining the adjustment of financial ratios. The coefficients of x_t for the equity-debt and sales-asset ratios are significant at ten percent level for about 80 percent of the firms in the sample. The coefficients of x_t for the rest of financial ratios are significant for about 50 percent to 60 percent of the firms in the sample. The next important variable is the financial ratio lagged for one period, y_{t-1}. The coefficients of this variable for various financial ratios are significant for about 40 percent to 60 percent of the firms in the sample. The variable of the financial ratio lagged for two periods, y_{t-2}, also plays a role in the ratio adjustment process. The sign of the coefficents of y_{t-2} for various ratios is negative for about 50 to 70 percent of the firms in the sample. The coefficients of y_{t-2} for the operating income-asset and equity-debt ratios are significant for about 30 percent of the firms in the sample. The coefficients of y_{t-2} for the rest of the financial ratios are significant for about 20 percent of the firms in the sample.

The results of OLS regressions are encouraging despite the high collinearity between y_{t-1} and y_{t-2}, and the potential serial correlation problem involved in the residual term. However, the regression results should be taken cautiously since the OLS estimates are biased and inconsistent. Also, the partial adjustment coefficient λ and adaptive expections coefficient δ cannot be identified uniquely from the OLS regression coefficient estimates. To obtain the unbiased, consistent and unique estimates of the structural parameters, the nonlinear regressions are employed.

Table 2 summarizes the cross-sectional distribution of parameter estimates based on the nonlinear regression. The parameters were also estimated using the log values of financial ratios. Since the results based on the log values of financial ratios are very similar to those in Table 2, they are not reported here.[7] Columns 1 through 6 show the distribution of parameter estimates and the associated t values. Column 7 reports the distribution of the coefficient of determination R^2. Eleven summary statistics are reported for each parameter estimate. They are the mean, standard deviation and 9 fractiles.

The overall results of nonlinear regressions show some evidence of both partial adjustment and adaptive expectations. The explanatory power of the model is relatively high, as indicated by the value of R^2. Most of the intercept estimates are very small and statistically insignificant. The estimated coefficients of partial adjustment (λ) and adaptive expectation (δ) are mostly falling into the relevant range between zero and one with very few exceptions.

The size of λ measures the speed of adjustment to the target ratio. The closer λ is to one, the faster the adjustment. When λ is less than one, the level of financial ratios will move only partially from the starting position to the desired (target) position. As indicated in Lev [1969], two major types of costs affect the degree of partial adjustment: the cost of adjustment and the cost of being out of equilibrium. The former often results from the technological, institutional and psychological inertia, and the increasing cost of rapid change. The latter often reflects the higher borrowing cost as a result of not conforming to the target.

The partial adjustment coefficients are higher for the current ratio, quick ratio and equity-debt ratio. The current and quick ratios involve current items which are expected to have smaller cost of adjustment. The result for the equity-debt ratio is slightly different from Lev's findings. This discrepancy may be explained by the recent trend of substituting short term debt for long term debt in the inflationary period. Several studies have documented the increasing use of short term debt.[8] The adjustment cost for short term debt is lower. Conceivably the adjustment speed will be higher as the proportion of short term debt increases. The partial adjustment coefficients for the sales-total assets, sales-inventory and net operating income-total assets ratios are lower possibly because the sales and inventory costs are not completely controlled by the managers.

The λ coefficients for the current ratio are significant (at ten percent level) for about 40 percent of the firms in the sample. The λ coefficients for the quick ratio, equity-debt ratio and sales-inventory ratio are significant for about 30 percent of the firms in the sample. The λ coefficients for the sales-total asset and return ratios are significant for about 20 percent of the firms.

The size of δ reflects the speed of expectation adjustment. The value of δ depends on the stability of target ratio or the persistency of changes in industry mean. In general, the lag of expectation adjustment is due to the uncertainty of current information. Therefore, the extent of expectation adjustment would seem to depend on the information structure of a particular financial ratio. The sales and profits are likely to be less stable because they are affected by the random factors of the economy and industrial segments. On the other hand, one would expect that the quick and current ratios are more stable because they are less affected by the complicated economic and industrial random factors.

The results in Table 2 confirm the existence of expectation adjustment lag. The adaptive expectation coefficients are generally higher for quick and current ratios and lower for the sales-total assets, equity-total debt and net operating income-total asset ratios. The adaptive expectation coefficients of current and sales-inventory ratios are significant (at ten percent level) for about 40 percent of the firms in the sample. For the remaining financial ratios, the adaptive expectation coefficients are significant for about 30 percent of the firms in the sample.

The error structure of the regression model was also examined. The first order autoregressive coefficients of the financial ratios are mostly small and insignificant. The nonlinear regression parameter estimates are in general not sensitive to the treatment of autocorrelation.[9] Since the cross-sectional distribution of parameter estimates is very similar to those reported in Table 2, the distribution of autoregressive parameter estimates is not reported here.

The explicit consideration of expectation lag has improved the explanatory power of the ratio adjustment model. The results in Table 2 suggest that the simple partial adjustment model is not appropriate when there exists random fluctuation in the industry means. Furthermore, the decomposition of total adjustment lag into two parts, with one caused by costs of adjustment and the other by information uncertainty, allows the financial analysts to see more clearly which factor contributes more to the adjustment lag.

Furthermore, the traditional partial adjustment model may overestimate the effect of adjustment costs on the speed of financial ratio adjustment. The average values of partial adjustment coefficients estimated by Lev range from .30 to .51, indicating a greater extent of the adjustment lag attributed to the costs of adjustment.[10] In contrast, Table 2 shows that the partial adjustment coefficients are in the range of .68 to .81 after the expectation lag is explicitly considered. The explanation for this discrepancy is simple. In the present model, the adjustment lag is attributed to the costs related to adjustment and being out of equilibrium, and random information; while in the simple partial adjustment model, the lag is attributed only to the costs of adjustment and of being out of equilibrium.

Predictions of Future Financial Ratios

Although the main purpose of this study is not directly concerned with the prediction of the future financial ratios, the usefulness of the generalized ratio adjustment model will be considerably limited if the model has very poor predictive ability. To provide some evidence on the forecasting power of the generalized ratio adjustment model, the average percentage prediction errors and mean square errors for the generalized model and Lev's model were calculated and compared. The prediction errors were computed by the following procedures. First, the value of future ratio was estimated based on the past ratios of a firm, the assumed adjustment process and an expectation of the future industry target ratio. The expected future industry target ratio was assumed to be x_{t-1}. Using x_{t-1}, y_{t-1}, y_{t-2} and the parameters estimated from the generalized partial adjustment-adaptive expectation model and Lev's partial adjustment model, the estimates of future ratio $\hat{y}_t$ were obtained from equations (1) and (8), respectively. Note that x_{t-1}

replaces x_t in equation (8) in calculating $\hat{y}_t$. Second, the prediction error was calculated as the difference between the actual ratio value y_t and the predicted value $\hat{y}_t$. Third, the average percentage prediction errors and mean square errors were computed.

Table 3 summarizes the mean and standard deviation of the percentage prediction errors (PPE) and mean square errors (MSE) for various financial ratios. As indicated, the generalized ratio adjustment model produces smaller percentage errors and mean square errors than Lev's model for all types of financial ratios except for the mean square error of sales-inventory ratio. In fact, the difference between the MSEs of the sales-inventory ratio for two alternative models is rather small (.6627 versus .6581). In general, the differences between the PPEs of two models are larger for the equity-total debts and net operating income-total assets ratios. The difference between the MSEs of two models is the largest for the equity-total debts ratio. The larger differences in forecasting errors generally occur for the financial ratios with relatively low adaptive expectation coefficients (δ). In contrast, for those ratios with higher expectation coefficients, the differences in the forecasting errors of the generalized model and Lev's model are relatively smaller. The findings in Table 3 indicate that the generalized ratio model has greater predictive ability because the lag of expectation adjustment is explicitly considered.

Table 3 also shows that the standard deviations of the percentage prediction errors are smaller for the generalized ratio adjustment model for four ratios. Hcwever, the standard deviations of the mean square errors are smaller for the generalized model for only three ratios. The overall results show that the generalized model provides slightly better forecasting efficiency (smaller standard deviations) than the partial adjustment model.

Industry and Size Effects

The preceding analysis is drawn based on a sample which includes firms from different industries and of different sizes. Recent studies have found that the choices of accounting procedures may vary across industries and firms of different sizes.[11] Since the selection of accounting procedures will ultimately affect the information reported in the financial statements, the time series process of financial ratios may therefore vary with industry and firm size. The causes of variations with industry and firm size have usually been attributed to contracting or political costs. For instance, large firms might tend to adjust ratios more quickly to industry averages than small firms to avoid public attention to abnormal performance. Zimmerman [1983] indicates that industry factor may also affect political costs. Firms in the same industry may face similar incentive problems and use similar contracting procedures.

To provide further information on the effects of industry category and firm size, the sample data were grouped by industry and firm size, and the same analytical procedure was applied to each group.

Table 4 reports the mean and standard deviation of λ and δ estimates by industry groups. The definition of group is based on the four-digit SIC codes. For quick ratio, all industry groups except the airline industry have λ and δ coefficients within one standard deviation of the total sample distribution. The airline industry exhibits higher partial adjustment coefficients λ and lower adaptive expectation coefficient δ. For current ratio, all industry groups have λ and δ coefficients within one standard deviation of the total sample distribution. However, the airline industry has relatively higher λ and lower δ coefficients. In addition, the grocery chain industry has the smallest λ coefficient. For equity-debt ratio, the chemical industry has the largest λ and the smallest δ. For sales-inventory ratio, the smallest λ is associated with the paper and forest product industry, and the largest λ goes to the textile industry. The δ coefficient for sales-inventory ratio has relative lower variations across groups with the textile industry having the lowest value of δ. For sales-asset ratio, the textile and paper industries have lower λ and the electronics industry has relatively lower δ. Both chemical and grocery chain industries have higher λ and δ. In general, the patterns of λ and δ distributions exhibit only small variations for sales-asset ratio. For net operating income-asset ratio the mineral and mining industry has the largest values of λ and δ. The paper and airline industries also have relatively higher λ and δ.

The overall results in Table 4 do not clearly indicate a unique industry effect on the adjustment pattern of all financial ratios. For instance, the airline industry has higher λ and lower δ for quick and current ratios but not for other ratios. Similarly, the textile industry have higher λ and lower δ for sales-inventory ratio but not for other ratios. However, results do indicate that for a particular financial ratio, there are some variations in the speed of adjustment across industries.

The total sample is next divided into two size groups based on the value of firm. The firm value is estimated as the sum of total market value of equity and book value of short and long term debts. Table 5 summarizes the mean and standard deviation of λ and δ estimates by firm size. For the partial adjustment coefficients, the large firm group has higher λ coefficients for all financial ratios except sales-inventory ratio. This suggests that large firms generally adjust their financial ratios more quickly than small firms. For the adaptive expectation coefficients, large firms have higher δ coefficients for quick ratio, equity-debt ratio and sales-asset ratio. Results indicate that large firms tend to adjust their expectations more quickly for only certain ratios. The t and F statistics were also computed to test the difference between group means and variances. The F-statistics are all insignificant, indicating that there is no significant difference in the dispersion (variances) of adjustment coefficients (λ and δ) between two groups. The t-statistics are significant (at ten percent level) for equity-debt and sales-asset ratios. For these two financial ratios, the large firm group has significantly larger speed of adjustment coefficient λ than the small firm group.

4. Summary

This paper extends Lev's partial adjustment model for financial ratios to consider explicitly the changes in management's expectations when the industry mean is highly variable. It introduces a process of adaptive expectations into the partial adjustment model to explain the dynamic adjustment of firm's financial ratio toward the industry norm. The proposed model provides a generalized framework for examining the nature of financial ratio adjustment when there exist both adjustment costs and information uncertainty.

The nonlinear regression method is used to estimate the structural parameters of the partial adjustment-adaptive expectations model. Results show that the managers do not always adjust their desired target ratio instantaneously when the industrial mean is subject to random changes. Rather, the managers gradually revise their desired target ratio by taking into account the fundamental change which is considered to be persistent. The paper finds that the size of the adaptive expectation coefficients varies across different financial ratios.

We also find that firm size and industry factors may affect the speed of financial ratio adjustment. Results show that large firms tend to adjust ratios more quickly than small firms. In contrast, large firms do not always adjust their expectations more quickly. Results also show that there are some variations in the ratio adjustment speed for different industries. However, results do not show a unique industry effect on the adjustment pattern of all financial ratios.

Results have two major implications for understanding accounting choices. First, while the adaptive model characterizes adequately the formation of target ratio expectations, there are variations across firms in the process of target forecasts. Since the selection of accounting rules depends on the expected accounting numbers or ratios (see Givoly [1985], and Moses [1987]), it is anticipated that accounting actions will also vary across firms. Results in this study support this contention in that estimated adaptive expectations coefficients vary across firms of different sizes and industry categories. Further research is needed to examine whether important firm-specific factors such as taxes, political costs, contractual relationships and ownership control may directly contribute to the variations in the process of forecasts. Second, the analysis of income smoothing involves the specification of a smoothing device and an expected earnings number. Previous studies (see Moses [1987]) on income smoothing have usually used a simple random walk model to estimate earnings expectations and to define the smoothing measure. The random walk model is a special case of the adaptive model when $\delta=1$. The findings in Givoly [1985] and this study suggest that the adaptive expectations model is more appropriate for estimating expected accounting numbers for analyzing smoothing behavior.

Footnotes

[1]When λ is equal to one, adjustment to the target ratio is instantaneous. The smaller the value of λ, the greater the adjustment lag. $(1-\lambda)$ is usually called the safety factor.

[2]Lev has also noted that equation (2) can be improved by setting $y_t^* = bx_{t-1}$. The coefficient b indicates that firms want to maintain a fixed deviation from the industry average.

[3]Such an expectation formation process is based on the idea that current expectation is derived by modifying previous expectation with currently available information. The extent of expectation revision depends on the persistency of current information.

[4]Equation (1') is based on the assumption that either the current value of industry mean is available or the firms can obtain an unbiased prediction of the current value of industry mean.

[5]An experiment with 10 firms selected by the alphabetical order showed that on average Gauss-Newton method used almost the same cpu time as Marquardt method.

[6]Nonlinear regression follows the same principle as linear regression in that parameters are selected to minimize the sum of residual square. See Draper and Smith [1966] for detailed discussions on various nonlinear regression methods.

[7]The results for the log values are available from the authors.

[8]See the findings reported in Taggart [1984] and Zwick [1977].

[9]The assumption on the normality of the stochastic disturbance term is less crucial for the nonlinear regressions. Malinvaud [1975] has shown that even without the assumption of normality on the disturbance term, the asymptotic distribution of the nonlinear regression estimates is normal and has the same mean and variance as the maximum likelihood estimates for the normal disturbance case.

[10]These figures are based on the results using x_{t-1} as the target level since Lev did not report the cross-sectional distribution of coefficient estimates obtained for x_t.

[11]See Watts and Zimmerman [1986], Zimmerman [1983] and Moses [1987].

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Table 1

Ordinary Least Squares Estimates of the Generalized Ratio Adjustment Model:

$$y_t = a_0 + a_1x_t + a_2y_{t-1} + a_3y_{t-2} + u_t$$

(Sample Period: 1965-1984, Sample Size N=112)

	$\hat{a}_0$	$t(a_0)$	$\hat{a}_1$	$t(a_1)$	$\hat{a}_2$	$t(a_2)$	$\hat{a}_3$	$t(a_3)$	R^2
ick Ratio									
an	-0.2028	-0.0865	0.8001	1.6089	0.3861	1.5846	-0.0451	-0.3114	0.4856
d. deviation	1.2566	1.5986	1.1125	1.5976	0.2667	1.0710	0.2451	1.1269	0.2368
actiles									
.1	-1.2163	-1.8543	-0.0976	-0.1530	0.0594	0.2639	-0.3507	-1.9771	0.1539
.2	-0.5639	-1.2962	0.0693	0.1939	0.1877	0.6771	-0.2609	-1.3090	0.2407
.3	-0.3258	-0.8769	0.2765	0.8074	0.2189	0.9385	-0.1934	-0.8961	0.3346
.4	-0.1944	-0.3943	0.4329	1.3130	0.2599	1.2146	-0.1291	-0.5368	0.4047
.5	-0.0516	-0.1666	0.6093	1.5235	0.3437	1.4485	-0.0401	-0.1385	0.4916
.6	0.1216	0.4199	0.7225	1.8854	0.4585	1.8189	0.0430	0.1660	0.5836
.7	0.2641	0.7021	0.9506	2.2852	0.5064	2.0047	0.0974	0.4040	0.6181
.8	0.5289	1.0522	1.1804	2.8233	0.6003	2.4562	0.1494	0.6909	0.6945
.9	0.7817	1.6752	1.5724	3.3659	0.7185	2.7939	0.2601	1.0749	0.7991
rrent Ratio									
an	-0.2703	-0.1783	0.7576	1.9145	0.3597	1.5012	-0.0234	-0.2831	0.5284
d. deviation	1.4884	1.6954	0.6952	1.5926	0.2551	1.0712	0.2278	1.1055	0.2519
actiles									
.1	-2.1428	-2.1037	0.0127	0.0393	0.0624	0.2886	-0.3584	-1.8354	0.1607
.2	-1.0436	-1.4278	0.2453	0.8027	0.1364	0.7370	-0.1879	-1.3843	0.2441
.3	-0.6786	-1.0443	0.3602	1.2654	0.2205	0.9439	-0.1366	-0.9380	0.3795
.4	-0.3134	-0.6886	0.4657	1.4451	0.2744	1.1697	-0.0965	-0.4192	0.4675
.5	-0.0518	-0.1315	0.6167	1.6959	0.3267	1.4026	-0.0099	-0.0435	0.5462
.6	0.1413	0.1786	0.7520	2.0603	0.4014	1.6097	0.0446	0.1765	0.6212
.7	0.4561	0.7036	0.9500	2.4422	0.4750	1.9627	0.0986	0.4165	0.6825
.8	0.6316	1.1905	1.2983	3.1634	0.5487	2.2100	0.1424	0.6234	0.7994
.9	1.4433	1.8805	1.6206	3.6385	0.6978	2.8319	0.2401	1.2043	0.8643
uity/Total Debts									
an	-0.1427	-0.4265	0.7936	3.2240	0.3734	1.7504	-0.0811	-0.7089	0.6947
d. deviation	0.7559	1.6094	0.7241	2.0405	0.2956	1.3216	0.2156	1.2939	0.1872
actiles									
.1	-0.8459	-2.7300	0.1103	0.6531	0.0002	0.0016	-0.3560	-2.2670	0.4134
.2	-0.4976	-1.8132	0.3007	1.5144	0.1513	0.7716	-0.2392	-1.8591	0.5333
.3	-0.3582	-1.3724	0.4068	2.1637	0.2308	1.0842	-0.1925	-1.3484	0.6031
.4	-0.1776	-0.8649	0.5196	2.7773	0.2576	1.3829	-0.1381	-0.6895	0.6518
.5	-0.0393	-0.3086	0.6307	3.1320	0.3536	1.6356	-0.0882	-0.5128	0.7402
.6	0.0319	0.1871	0.7538	3.4956	0.3904	1.9080	-0.0221	-0.1485	0.8012
.7	0.0937	0.4795	0.8568	4.0366	0.4885	2.2134	0.0449	0.1756	0.8268
.8	0.2918	0.9717	1.1269	4.6836	0.5247	2.5213	0.0891	0.5278	0.8532
.9	0.6531	1.7097	1.4873	5.4866	0.7274	3.3838	0.1643	1.2135	0.9010

Table 1 (continued)

	$\hat{a}_0$	$t(a_0)$	$\hat{a}_1$	$t(a_1)$	$\hat{a}_2$	$t(a_2)$	$\hat{a}_3$	$t(a_3)$	
Sales/Inventory									
Mean	-1.5753	-0.3386	0.7486	1.9218	0.4335	1.7252	-0.0395	-0.3500	0
Std. deviation	11.4524	1.6962	0.7913	1.6210	0.3385	1.4100	0.2627	1.0787	0
Fractiles									
.1	-10.1616	-2.6753	0.0116	0.0844	-0.0441	-0.1464	-0.3803	-1.7401	0
.2	-6.8159	-1.9328	0.1953	0.5521	0.1485	0.4892	-0.2440	-1.2564	0
.3	-3.7829	-1.1881	0.3051	1.0558	0.2370	0.9252	-0.1977	-0.9113	0
.4	-1.8385	-0.8040	0.3958	1.3333	0.3308	1.1748	-0.1292	-0.5596	0
.5	-0.5813	-0.2107	0.5448	1.7869	0.4205	1.6351	-0.0817	-0.3346	0
.6	0.7318	0.3603	0.7368	2.1706	0.5232	2.0329	-0.0175	-0.0622	0
.7	1.5484	0.7327	0.8751	2.6385	0.6416	2.3507	0.0884	0.3672	0
.8	2.9566	1.1895	1.1253	3.1085	0.7177	2.9623	0.2017	0.7650	0
.9	4.9422	1.4580	1.7933	4.0090	0.8313	3.5457	0.2673	1.0191	0
Sales/Total Assets									
Mean	-0.2192	-0.3170	0.7471	2.7640	0.4911	2.0953	-0.8056	-0.5875	0
Std.deviation	0.9654	1.8877	0.6660	2.1363	0.2971	1.2571	0.2739	1.3240	0
Fractiles									
.1	-1.4589	-2.4581	-0.0808	-0.1277	0.0932	0.5099	-0.4211	-2.0313	0
.2	-0.7973	-1.9018	0.3157	1.2985	0.2417	0.9263	-0.3085	-1.7292	0
.3	-0.5210	-1.3609	0.4495	1.7836	0.3361	1.4559	-0.2375	-1.2050	0
.4	-0.2805	-0.9687	0.5927	2.2570	0.4086	1.8590	-0.1593	-0.8483	0
.5	-0.0905	-0.4520	0.6871	2.7309	0.4780	2.0404	-0.0922	-0.5024	0
.6	0.0158	0.0548	0.7974	3.1307	0.5847	2.4726	-0.0355	-0.2337	0
.7	0.1074	0.3581	0.9670	3.4147	0.6622	2.8147	0.0591	0.2266	0
.8	0.3451	1.0898	1.1592	3.9584	0.7249	3.0598	0.1302	0.6414	0
.9	0.5793	2.0234	1.5980	5.2979	0.8980	3.5367	0.2569	1.0917	0
Net Operating Income/Total Assets									
Mean	-0.0114	-0.3211	0.8035	2.6721	0.4470	1.9968	-0.1427	-0.7043	0
Std. deviation	0.0686	1.5883	0.6329	2.0179	0.2998	1.3951	0.2309	1.1591	0
Fractiles									
.1	-0.0747	-2.0324	0.1275	0.4195	0.0536	0.2599	-0.4647	-2.4794	0
.2	-0.0386	-1.5178	0.3466	1.0737	0.1634	0.6625	-0.3810	-1.6927	0
.3	-0.0333	-1.2283	0.4980	1.4771	0.2884	1.2108	-0.2468	-1.4089	0
.4	-0.0235	-0.8226	0.5893	1.8906	0.3797	1.7002	-0.1962	-0.8583	0
.5	-0.0119	-0.4364	0.7041	2.3673	0.4370	1.9036	-0.1577	-0.6609	0
.6	-0.0013	-0.0387	0.8946	2.9056	0.5067	2.2561	-0.0636	-0.3216	0
.7	0.0153	0.4094	1.0114	3.9206	0.5721	2.6388	0.0099	0.0396	0
.8	0.0315	0.7859	1.2605	4.6099	0.6695	3.1089	0.0834	0.3813	0
.9	0.0606	1.5937	1.5410	5.5180	0.9056	3.6596	0.1496	0.5953	0

Note: y_t = a firm's financial ratio in year t,
x_t = the industry average of a particular financial ratio in year t,
y_{t-1} = a firm's financial ratio lagged by one year (t-1),
y_{t-2} = a firm's financial ratio lagged by two years (t-2),
u_t = the disturbance term of the regeression model, and
a_i, i = o,1,2, and 3 represent intercept and regression coefficients, respectivel

Table 2

Nonlinear Regression Estimates of the Generalized Ratio Adjustment Model:

$$y_t = a_0 + \lambda\delta x_t + (2-\lambda-\delta)y_{t-1} - (1-\lambda)(1-\delta)y_{t-2} + u_t$$

(Sample Period: 1965-1984, Sample Size N=112)

	a_0	$t(a_0)$	$\hat{\lambda}$	$t(\lambda)$	$\hat{\delta}$	$t(\delta)$	R^2
Quick Ratio							
Mean	0.0058	-0.1770	0.8053	1.5639	0.8459	1.4502	0.9590
Std. deviation	0.2779	1.2727	0.3223	2.1856	0.3262	2.0296	0.0348
Fractiles							
.1	-0.2709	-1.6986	0.3813	0.0087	0.3235	0.0087	0.9181
.2	-0.2103	-1.2045	0.5456	0.0254	0.5040	0.0256	0.9383
.3	-0.0978	-0.0806	0.6428	0.0390	0.6952	0.0383	0.9536
.4	-0.0504	-0.0398	0.7428	0.0514	0.7479	0.0513	0.9622
.5	-0.0300	-0.0249	0.7825	0.0299	0.8479	0.0807	0.9609
.6	0.0132	0.0051	0.8730	1.1329	0.8827	1.0233	0.9734
.7	0.0620	0.0190	0.9248	1.6951	0.9642	1.9071	0.9778
.8	0.1430	0.0623	1.0211	2.9424	1.1028	2.8718	0.9840
.9	0.3199	1.0001	1.2740	5.3631	1.2524	4.4716	0.9889
Current Ratio							
Mean	0.0239	-0.1927	0.7846	1.6919	0.8523	1.8467	0.9746
Std. deviation	0.4206	1.2504	0.3600	2.2151	0.3320	2.1608	0.0234
Fractiles							
.1	-0.4318	-1.9070	0.2456	0.0116	0.3790	0.0155	0.9679
.2	-0.2641	-1.2556	0.4114	0.0234	0.6248	0.0232	0.9645
.3	-0.1656	-0.2270	0.6196	0.0408	0.6553	0.0401	0.9726
.4	-0.0983	-0.0400	0.2129	0.0819	0.7616	0.0736	0.9775
.5	-0.0247	-0.0076	0.7825	0.9730	0.8280	1.1061	0.9808
.6	0.0317	0.0167	0.8566	1.6340	0.9069	1.9421	0.9337
.7	0.0922	0.0363	0.9308	2.1104	1.0038	2.5104	0.9862
.8	0.2606	0.2529	1.0707	2.8017	1.1461	3.8666	0.9909
.9	0.4958	1.0132	1.3339	4.9404	1.3411	5.5671	0.9925
Equity/Total Debts							
Mean	0.0351	-0.5107	0.8105	1.5038	0.7803	1.2217	0.8821
Std. deviation	0.6719	1.2289	0.3074	2.0456	0.3028	1.6150	0.0974
Fractiles							
.1	-0.5700	-2.3905	0.3796	0.0137	0.3253	0.0130	0.7637
.2	-0.3975	-1.6662	0.5778	0.0297	0.5209	0.0254	0.8369
.3	-0.2998	-0.5907	0.6640	0.0445	0.6769	0.0437	0.8681
.4	-0.1900	-0.0752	0.7177	0.0620	0.7593	0.0593	0.8917
.5	-0.1163	-0.0448	0.8442	0.1264	0.8419	0.1164	0.9047
.6	-0.0338	-0.0144	0.8919	1.0380	0.9104	0.9535	0.9253
.7	0.0938	0.0137	0.9802	1.9152	0.9687	1.9742	0.9410
.8	0.4780	0.0422	1.0665	3.1736	1.0079	2.8755	0.9500
.9	0.9802	0.1662	1.2534	4.8235	1.0835	3.7239	0.9636

Table 2 (continued)

	$\hat{a}_0$	$t(a_0)$	$\hat{\lambda}$	$t(\lambda)$	$\hat{\delta}$	$t(\delta)$	R^2
Sales/Inventory							
Mean	-1.0646	-0.4761	0.7356	1.5370	0.8153	1.7593	0.9677
Std. deviation	10.2483	1.7893	0.3616	2.2665	0.3020	2.2027	0.0381
Fractiles							
.1	-3.3984	-3.6945	0.2201	0.0069	0.4525	0.0090	0.9207
.2	-1.4194	-0.9398	0.4089	0.0175	0.5476	0.0211	0.9472
.3	-0.7975	-0.1197	0.5042	0.0391	0.6543	0.0401	0.9620
.4	-0.4413	-0.0453	0.6096	0.0499	0.7623	0.0659	0.9729
.5	-0.1675	-0.0119	0.7767	0.1978	0.8386	0.4999	0.9803
.6	0.0322	0.0044	0.8421	1.0206	0.8918	1.6338	0.9866
.7	0.5318	0.0274	0.9198	1.6217	0.9555	2.4725	0.9911
.8	1.6235	0.1256	1.0067	3.0585	1.0142	3.6524	0.9930
.9	2.8147	0.9767	1.2594	4.6675	1.1517	5.2113	0.9946
Sales/Total Assets							
Mean	0.0151	-0.2902	0.6813	1.2461	0.7944	1.4561	0.9846
Std. deviation	0.3130	1.4832	0.3016	1.9536	0.2641	1.8516	0.0160
Fractiles							
.1	-0.3148	-2.2583	0.2757	0.0167	0.5215	0.0166	0.9642
.2	-0.2004	-0.9665	0.4716	0.0327	0.6025	0.0325	0.9750
.3	-0.1257	-0.0681	0.5599	0.0435	0.6537	0.0439	0.9818
.4	-0.0503	-0.0366	0.6228	0.0678	0.6958	0.0659	0.9859
.5	-0.0046	-0.0048	0.6864	0.1071	0.7450	0.1059	0.9898
.6	0.0334	0.0191	0.7381	0.7763	0.8079	1.1067	0.9927
.7	0.0886	0.0552	0.7923	1.3105	0.9024	2.1496	0.9940
.8	0.1530	0.1809	0.9115	2.1076	1.0485	3.1416	0.9965
.9	0.3790	0.9634	1.0438	3.9211	1.1701	4.2864	0.9976
Net Operating Income/Total Assets							
Mean	0.0000	-0.0439	0.7543	0.7743	0.8023	0.8990	0.9061
Std. deviation	0.0271	0.8811	0.2468	1.3018	0.2454	1.5072	0.1038
Fractiles							
.1	-0.0317	-1.1375	0.4011	0.0087	0.4874	0.0087	0.7875
.2	-0.0234	-0.0893	0.5432	0.0174	0.6180	0.0175	0.8420
.3	-0.0132	-0.0533	0.6603	0.0314	0.6894	0.0315	0.9005
.4	-0.0079	-0.0241	0.7314	0.0386	0.7518	0.0385	0.9281
.5	-0.0015	-0.0079	0.7720	0.0556	0.8036	0.0564	0.9515
.6	0.0023	0.0092	0.8262	0.0763	0.8541	0.0757	0.9584
.7	0.0098	0.0268	0.8863	0.4224	0.9362	0.7126	0.9636
.8	0.0178	0.0601	0.9675	1.6702	1.0098	1.8424	0.9745
.9	0.0303	0.4365	1.0256	2.9014	1.0786	3.5164	0.9831

Note: a_0 = intercept,
λ = the speed of ratio adjustment coefficient,
δ = the speed of expectation adjustment coefficient,
$\hat{\lambda}$ and $\hat{\delta}$ are the regression estimates of λ and δ, and
y_t, x_t, y_{t-1}, y_{t-2}, and u_t are defined as in Table 1.

Table 3

Summary Prediction Errors for the Generalized Ratio Adjustment Model and Lev's Partial Adjustment Model[a]

(Sample Period: 1965-1984, Sample Size N=112)

	Generalized Model		Partial Adjustment Model	
	Mean	Std. Deviation	Mean	Std. Deviation
Quick Ratio				
PPE[b]	.1632	.1145	.1712	.1199
MSE[c]	.0949	.2655	.0985	.2535
Current Ratio				
PPE	.1183	.0626	.1256	.0672
MSE	.1691	.3757	.1839	.3765
Equity/Total Debts				
PPE	.4509	.3804	.4694	.3737
MSE	.5864	1.6611	.6342	1.6659
Sales/Inventory				
PPE	.0847	.0391	.1289	.1135
MSE	.6627	.5222	.6581	.4993
Sales/Total Assets				
PPE	.0919	.0652	.0954	.0636
MSE	.0436	.0970	.0469	.1085
Net Operating Income/Total Assets				
PPE	.4277	.4202	.4607	.4464
MSE	.0014	.0021	.0015	.0019

[a] The prediction errors e_t are estimated as follows:

(i) For the generalized ratio adjustment model:

$$e_t = y_t - \hat{a}_0 - \hat{\lambda}\hat{\delta}x_{t-1} - (2-\hat{\lambda}-\hat{\delta})y_{t-1} + (1-\hat{\lambda})(1-\hat{\delta})y_{t-2}$$

(ii) for Lev's partial adjustment model:

$$e_t = y_t - \hat{\beta}_0 - \hat{\beta}_1 x_{t-1} - \hat{\beta}_2 y_{t-1}$$

where β_0 is the intercept, and $\hat{\beta}_1$ and $\hat{\beta}_2$ are the regression coefficients of Lev's partial adjustment model, and e_t is the residual error. All remaining variables are defined as in Tables 1 and 2.

[b] PPE = percentage prediction errors.

[c] MSE = mean square errors.

Table 4

Nonlinear Regression Estimates of Partial Adjustment and Adaptive Expectation Coefficients by Industry Groups*

(Sample Period: 1965-1984, Sample Size N=112)

Industry Group	Quick Ratio		Current Ratio		Equity/ Total Debts		Sales/ Inventory		Sales/ Total Assets		Net Operating Income/ Total Assets	
	$\hat{\lambda}$	$\hat{\delta}$	$\hat{\lambda}$	$\hat{\delta}$	$\hat{\lambda}$	$\hat{\delta}$	$\hat{\lambda}$	$\hat{\delta}$	$\hat{\lambda}$	$\hat{\delta}$	$\hat{\lambda}$	$\hat{\delta}$
Textile	.7305 (.3289)	.8848 (.3441)	.7575 (.3741)	.8725 (.3387)	.6985 (.3132)	.8106 (.2278)	.9292 (.2106)	.6732 (.2306)	.6076 (.3365)	.7475 (.3079)	.6941 (.1927)	.6348 (.2217)
Paper & Forest Product	.7451 (.2974)	.8536 (.2667)	.8124 (.3171)	.8068 (.2767)	.7460 (.2286)	.8341 (.3792)	.6540 (.3273)	.8546 (.2514)	.6108 (.3503)	.7678 (.3430)	.8369 (.1708)	.8448 (.2699)
Chemical	.7908 (.3452)	.8838 (.3386)	.7439 (.3925)	.9321 (.2971)	1.0584 (.1805)	.6872 (.3691)	.7492 (.3694)	.8543 (.3194)	.7462 (.1770)	.8609 (.2216)	.7234 (.2179)	.7648 (.2013)
Oil	.8069 (.2489)	.9156 (.3041)	.8075 (.3302)	.9251 (.2935)	.8015 (.2920)	.7779 (.2818)	.6737 (.4309)	.8517 (.3030)	.6946 (.3179)	.8241 (.2139)	.6851 (.2896)	.7941 (.2811)
Mineral & Mining	.7204 (.3381)	.8104 (.3549)	.7689 (.3339)	.7962 (.3797)	.7505 (.3899)	.7708 (.3528)	.7635 (.3354)	.7823 (.3245)	.7295 (.3829)	.8097 (.2863)	.9015 (.2001)	.9355 (.1651)
Electronics	.6635 (.3238)	.7709 (.3053)	.7360 (.3371)	.7676 (.4159)	.8002 (.4008)	.7904 (.2975)	.7059 (.4942)	.8547 (.3348)	.6772 (.3222)	.6979 (.3329)	.7488 (.1777)	.7680 (.1863)
Airline	1.1507 (.3422)	.4985 (.2465)	.9638 (.5057)	.7290 (.3530)	.8880 (.2121)	.7875 (.3075)	.7448 (.2043)	.8518 (.2213)	.6549 (.2164)	.7723 (.1787)	.8027 (.3162)	.8903 (.2439)
Grocery Chain	.8810 (.2837)	.7119 (.3501)	.6294 (.3465)	.8976 (.4045)	.8905 (.3642)	.7607 (.2118)	.7589 (.3882)	.7470 (.4558)	.7574 (.2285)	.8429 (.2418)	.6915 (.2959)	.7919 (.2347)

* Standard deviations are included in the parentheses. $\hat{\lambda}$ and $\hat{\delta}$ are estimated from the model in Table 2. λ is the speed ratio adjustment coefficient and δ is the speed of expectation adjustment coefficient.

Table 5

Nonlinear Regression Estimates of Partial Adjustment (λ) and Adaptive Expectation (δ) Coefficients by Firm Size†

(Sample Period 1965-1984, Sample Size N=112)

	Small Firms (N=56)	Large Firms (N=56)	
Quick Ratio			
$\hat{\lambda}$	.8045	.8059	t = .0229
	(.3211)	(.3262)	F = 1.0320
$\hat{\delta}$	.8064	.8254	t = .3074
	(.3428)	(.3113)	F = 1.2125
Current Ratio			
$\hat{\lambda}$	.7689	.8003	t = .4601
	(.3686)	(.3537)	F = 1.0855
$\hat{\delta}$	.8720	.8324	t = -.6305
	(.3351)	(.3306)	F = 1.0274
Equity/Total Debts			
$\hat{\lambda}$	.7521	.8868	t = 2.3715**
	(.3117)	(.2903)	F = 1.1532
$\hat{\delta}$	.7653	.7953	t = .5235
	(.2923)	(.3148)	F = 1.1592
Sales/Inventory			
$\hat{\lambda}$	.7714	.6997	t = -1.0497
	(.3490)	(.3735)	F = 1.1453
$\hat{\delta}$	.8300	.8004	t = -.5183
	(.3189)	(.2860)	F = 1.2435
Sales/Total Assets			
$\hat{\lambda}$	.6340	.7284	t = 1.6738*
	(.2871)	(.3104)	F = 1.1686
$\hat{\delta}$	.7859	.8029	t = .3400
	(.2512)	(.2782)	F = 1.2250
Net Operating Income/Total Assets			
$\hat{\lambda}$	.7420	.7666	t = .5267
	(.2347)	(.2597)	F = 1.2254
$\hat{\delta}$	.8118	.7926	t = -.4129
	(.2532)	(.2392)	F = 1.1206

†Standard deviations are included in the parentheses. $\hat{\lambda}$ and $\hat{\delta}$ are estimated from the model in Table 2. The critical value of F(55,55) is 1.53 at 5% level.

*Significance at 10% level, t(.05,110) = 1.671.

**Significance at 5% level, t(.025,110) = 2.000.